Pattern Based Motion for Crowd Simulation

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Abstract. We present a pattern-based approach for simulating the steering behavior of pedestrians, which aims to imitate the way that real pedestrians perceive spatial-temporal information and make steering decisions in daily-life situations. Novel representations of spatial-temporal patterns are proposed that allow modelers to intuitively and naturally specify some prototypical patterns for various steering behaviors. Based on the spatial-temporal patterns, a hierarchical pattern matching process has been developed, which simulates how pedestrians process spatial temporal information and make steering decisions. Experimental results show that this new approach is quite promising and capable of producing human-like steering. We hope that the idea presented in this paper can direct researchers in this area with a fresh perspective.

Keywords: steering behavior, spatial-temporal patterns, crowd simulation, motion planning

1 Introduction

Simulation of pedestrian navigational behaviors has a wide range of applications in crowd simulation, digital entertainment, and safety planning etc. Although humans are able to move smoothly almost effortlessly even in crowded places, it is still a challenging task for computer programs to imitate such behaviors realistically.

From a computational modeling point of view, the complex navigational behaviors are typically generated from activities of an agent at two levels: *path planning* and *locomotion*. Path planning can be considered as the higher-level behavior that generates a global path directing the agent to the goal. This typically considers static aspects of the environment, such as walls and doorways. Locomotion is considered as the lower-level behavior that actuates the agent's motion in order to avoid dynamic obstacles. This bi-level methodology is effective in some applications, but is lacking when it comes to the generation of realistic human motion. Our work describes a level between the traditional two, which uses higher-level cognitive information to adjust routes dynamically. These adjustments essentially try to reduce the likelihood of collisions by adopting strategies. Our work focuses on this middle level by describing and modeling *strategic steering behaviors*.

In real life, strategic steering behaviors are commonly observed during pedestrians' navigation. Pedestrians will use the strategies to ensure their movement is smooth and efficient in avoiding collisions. However, we argue that such phenomenon does not necessarily reflect any smart mechanism to guarantee collision-free movement. In fact, we believe that pedestrians do not need to make complex decisions in most situations. Instead, they are adapted to relying on simple steering strategies corresponding to different situations that they are familiar with. One characteristic of such strategic steering behaviors, which distinguishes it from locomotive movement, is that proactive planning is involved. When comparing to path planning, the steering strategies generally consider sequences of actions in relative short term of both space and time.

Most existing agent-based approaches rely on various mechanical or steering rules to prevent agents from colliding with each other. There are two major disadvantages of this approach: 1) rules are specific to different situations and are hard to design, it is difficult to naturally relate these rules with human behaviors; 2) the realism of the generated behaviors is largely determined by the experience of the designer which needs significant effort in tuning the parameters involved.

We adopt a different approach. Our work is motivated by some basic assumptions which are based on our observations and existing literature on pedestrian behaviors. It seems that pedestrians achieve efficient steering behaviors relying on certain implicit criteria to assist their decision. Such criteria need to reflect the current situation comprehensively while in a sufficiently simple and aggregated form such that it leads to fast decisions efficiently. We regard such implicit criteria as the formed *patterns* in our work. We assume that experienced pedestrians proactively match the perceived spatial-temporal patterns in the situation with some prototypical cases in their experience to retrieve similar steering strategies and apply them in an empirical way.

The major advantages of this pattern-based approach include: 1) *Intuitiveness*: it allows modelers to understand and specify patterns intuitively ac-cording to their experience; 2) *Efficiency*: complex steering behaviors can be achieved through proper scheduling among several simple steering strategies based on the pattern-matching results; and 3) *Human-like information processing*: human are efficient in processing information through grouping [1]. Consequently, they are capable of handling more chunks of information at the same time in a parallel manner. In our approach, spatial-temporal information is implicitly processed in a parallel manner and represented in an aggregated form (3D array). The patterns are capable of handling incomplete information through the proposed hierarchical pattern matching process.

In our previous work [2], we have proposed a generic framework based on this pattern-based approach. In this paper, we will focus on the design of the spatial-temporal patterns based on the agents attention in 2-dimensional space along a period of time. The pattern-matching process is hierarchical along both spatial and temporal domains, with differing significance defined by the proposed attention model, which can better imitate the decision making process of human beings.

The rest of the paper is organized as follows: Section 2 describes related work on steering behavior modeling. The pattern-based framework will be reviewed in Section 3. The design on the spatial-temporal patterns is detailed in Section 4. Section 5 describes the hierarchical matching process and includes a concrete example of the pattern-matching process. Simulation results that demonstrate the unique features and capabilities of the approach are shown and discussed in Section 6. Section 7 concludes the paper and outlines ideas for future work.

2 Related Work

There have been many attempts to simulate peoples steering behaviors ever since Reynolds pioneering work on *boids* [3]. As one of the essential goals, collision avoidance plays an important role in these works. As motion control and motion planning [4–6] have been broadly studied, most previous work focuses on generating optimal, collision-free motion for all entities in the simulation environment. One representative work is the *Reciprocal Velocity Obstacle (RVO)* model [4] and its variants [7–9]. It generally provides a single optimal solution for all cases. However, we argue that humans are non-optimal in their movement behavior. For example, collisions do occur in some real world situations.

Another popular approach, rule-based models [10–15] achieve collision avoidance based on pre-defined rules. Depending on the tightness of the rules, collisions may occur and visually appealing simulation is achievable through careful tuning of the rules. However, rules are likely tightly coupled to specific scenario conditions, thus such models may not function well in general. It also poses a challenge for the modelers to specify a complete set of rules capable of generating realistic simulation results for many different situations.

Example-based approaches have been proposed and applied in steering behavior simulation recently [16, 17]. Real-life examples of the moving trajectories of people are recorded, extracted and stored as the input to a simulation model. Agents in the simulation analyze the simulation environment and compare it with the stored examples. Certain stored moving trajectories in the example situations are applied. Although this work focused on replicating realistic steering behaviors, the model realism is limited as paths for agents are explicitly synthesized. Only external factors can be extracted from the image or video based examples, unique traits of individual persons are difficult to incorporate with this approach.

There is currently a trend to incorporate different cognitive components of human into behavioural modeling aiming to achieve higher level of realism. [18–21] focus on *psychological factors*, [22] integrates *emotion* in the Recognition-Primed Decision-making (RPD) Model. In [23], *prediction* is taken into account and [24] uses *egocentric affordance field* for space-time planning in short term. [25] follow a *visual stimuli/motor response* control flow by taking captured image from the real world as input to form the visual stimuli. These models demonstrate a good perspective in modeling pedestrian behaviors, that is the realism of the model. These models aim to generate realistic human-like behaviors based on a *naturalistic* decision-making mechanism [26].

3 Pattern-based Decision-Making Framework

In our previous work, we have proposed a pattern-based decision-making framework based on assumptions that try to describe and explain how real pedestrians navigate through crowds [2]. In this section, we review the previously described framework and highlight those parts that have been re-designed or further developed. It is assumed that pedestrians proactively adopt a limited number of steering strategies to minimize the chances of performing certain reactive or instinctive reactions to resolve imminent collisions. The scheduling and execution of these steering strategies result in various complex navigational behaviors of individual pedestrians. Decisions on selection and execution of steering strategies in a given situation, and at a specific moment in time are based on the matching results between the currently perceived patterns and the prototypical cases in their experience base. The overall cognitive process is modelled as a continuous process following the perceive-decide-act paradigm as shown in Figure 1.

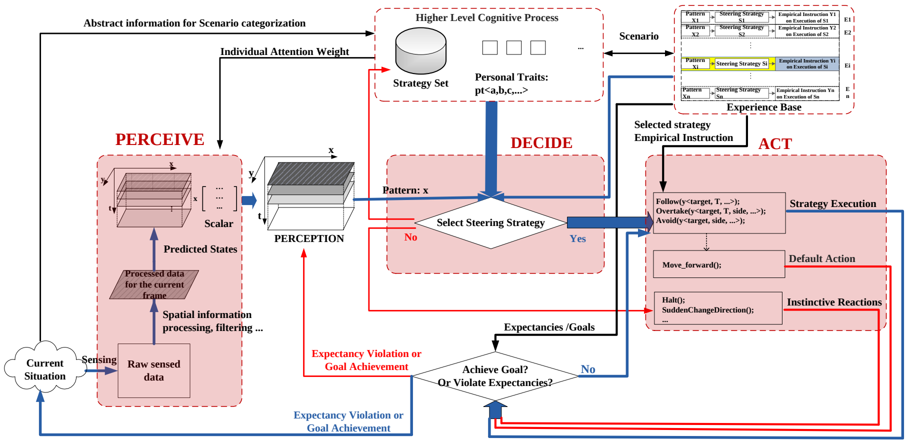


Fig. 1. Overview of the pattern-based decision-making framework

In the framework, an agent first senses the current situation from its vision, and the raw sensed data are further processed and filtered by the attention system. Prediction is involved to generate comprehensive *perception* on the spatial configuration of the current situation along a predicted period of time. The agent then extracts useful spatial-temporal information from the perceptual data as *patterns* to assist its understanding of the current situation. The agent then matches these patterns against prototypical cases in its *experience base*. The commonly used steering strategy and empirical instructions for the execution of the steering strategy are associated with the corresponding prototypical case as a specific experience instance in the experience base. The experience base is used to model the working memory of a pedestrian during his/her navigation, where only a limited set of steering strategies commonly applicable to the current situational context are retrieved from the long term memory through some higher level cognitive process.

Different strategy sets should be retrieved for different contexts. However, the retrieval of specific steering strategy sets corresponding to different contexts is not the focus of this paper. We will demonstrate the pattern-matching process based on a given steering strategy set for a restricted bi-directional passageway context. For this context, our model currently includes three steering strategies: *follow*, *overtake* and *side-avoid*. They are commonly observed in pedestrians steering behaviors in daily life.

The scheduling of strategies from the steering strategy set is realized through a series of strategy selections along a simulation period. The selection of specific steering strategy at a given time instance is not only based on the pattern-matching results as mentioned above. It is also influenced by certain internal factors such as *personal traits*. Particularly in this work, we consider the *commitment levels* to their strategic plan and their *preferred speed* for agents. For example, agents with lower commitment level will start to execute a steering strategy upon a relatively low degree of matching of the perceived pattern with prototypical cases in experience. Consequently, they may change their strategy more frequently to accommodate the dynamic crowd in the situation. On the other hand, agents with higher commitment level are more considerate about their strategic plan. They will not start to execute a steering strategy until they gain enough confidence from a relatively high degree of pattern matching. As a result, more smooth steering trajectories are emerged from these agents. Through such factors, our model can be integrated with some higher-level cognitive model to generate more complex behaviors.

In the abstract framework level, our current framework is highly consistent with the well-known *Recognition-Primed Decision (RPD)* model, which is a proper model to reflect naturalistic decision-making process of human [26]. Each experience instance consists of a pattern (cues in RPD terms) and a steering strategy. The steering strategy is characterized by the empirical instructions on how to execute the steering strategy in a specific situation corresponding to the prototypical pattern. Goals, expectations and actions in RPD terms are included in the empirical instructions to represent different experience levels of individual agents on how they behave in terms of steering behaviors. An agent has two states, one in which a steering strategy is selected and one in which no steering strategy is selected. When no steering strategy is matched, the patterns (cues) will be used to select a matching strategy. Once a strategy is selected, matching is no longer necessary. Instead, the selected steering strategy is executed according to the empirical instructions until such time as the expectancies are violated or the goals have been achieved. Iterations of sensing, perception, steering strategy selection (when necessary) and execution continue in the simulation. An important new feature of the current framework compared with the previously designed one is the use of violation-check during the strategy execution process in our model as shown in Figure 1. Perception formation and the pattern-matching process only occur when a new steering strategy needs to be made due to the violation of the current strategy. We argue this may reflects the naturalistic decision-making process of humans as assumed in the RPD model as well. In real life, people are likely to choose a course of action (steering strategy) and continue with that course until they find the current situation is no longer consistent with what they expect. As a result, relative smooth trajectories for individual pedestrians in their steering process are often observed.

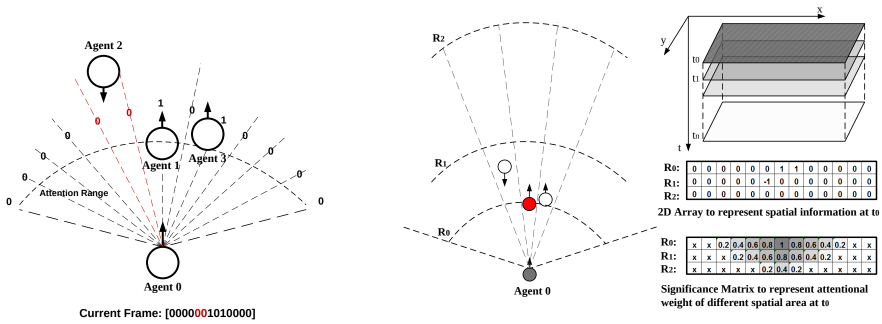
4 Spatial-Temporal Patterns

4.1 Design Requirements

In our framework, patterns function as the implicit criteria to assist agents make fast decisions during steering strategy selection and execution. To utilize such functions, the design of patterns needs to meet two requirements:

1. The designed patterns need to reflect useful spatial and temporal information that is used in the decision-making process *comprehensively.* More specifically, they should be comprehensive in a way that:
   (a) Sufficient information is captured. For example, not only the spatial information at the current moment needs to be captured, the change of such information along a short period of time should also be considered to imitate the prediction of human.
   (b) Significance of information is considered at different positions along both the spatial and temporal domains based on their impact on the decision-making process. For example, information immediately in front of the agent is assumed to be more influential than information gathered from its visual peripherals.
   (c) Information in the situation is processed in a bulk/parallel manner. Pedestrians seem capable of forming situation assessment quickly with just a glance at the environment. We believe this is because humans naturally group information and process groups of information in a bulk/parallel manner rather than to process each element in a sequential manner.
2. The representation of the patterns should be sufficiently *succinct* such that it is feasible to achieve fast and efficient decisions. The patterns also naturally reflect some qualitative criteria that are commonly used by pedestrians rather than precise computations to make steering choices. Thus, modelers can design these patterns intuitively based on their experience. This is one of the major advantages of our pattern-based approach compared with most existing rule-based models.

In summary, the designed pattern should be comprehensive in its content and succinct in its representation. To achieve the goal of collision avoidance in the steering behavioural level, information on the potential obstacles (static objects or dynamic agents) in both spatial and temporal domains needs to be captured. The spatial information is predominantly processed through visual sensing and attention filtering; the temporal information is generally formed through predicted change on the spatial information.



(a) Drawbacks of the single attention range representing 1D spatial information

(b) Multi-Level attention range capturing 2D spatial Information with differing significances along spatial and temporal domains

Fig. 2. The previous and the current attention systems

In previous work [2], we proposed a novel array-based representation for the situation awareness and defined spatial-temporal patterns in the form of a 2D array (1D spatial + 1D temporal) as shown in Figure 2(a). The spatial information in the previous work is represented by a 1D array with values 0, 1(-1) representing available space, obstacles with same (or opposite) moving directions respectively within the attention range of the agent on a relative visionary direction represented by a column. The model oversimplifies the perceived patterns in 1D space based on the single attention range value. Such 1D spatial patterns obviously lose some useful information that may result in different decisions during navigation.

4.2 Perception

To mimic the attention range realistically, we have made three assumptions in the use of attention for human in real life:

1. People tend to pay more attention to the area immediately in front of them within a relatively short visual range.
2. People tend to consider currently relevant information with higher significance as opposed to any future predictions.

3. People may pay more attention to some salient features such as size, colour of certain objects in the situation.

Based on the assumed rules above, we have designed the patterns to reflect information from the situation more comprehensively while trying to keep its representation succinct. Specifically, we have the following implications from the above rules in defining patterns:

1. Patterns are defined based on 2D spatial information with significance difference for different area in spatial and temporal domains.
2. The significance of an area is inversely proportional to its relative distance to the agent, its relative deviation from the agents vision center, and how further ahead it is predicted.
3. A scalar matrix to represent different visual impact based on the saliency features of the situation can also be considered in the pattern recognition process. Due to the length limit, we do not specify the details in the paper.

As a result, we have the spatial-temporal perception based on a multi-level attention range designed as shown in Figure 3. A 2D array is generated to represent the spatial information at a particular simulation time t_0 as shown in Figure 2(b). A 3D array is aggregated from several such 2D arrays based on a simple linear dead reckoning method to model the dynamic change of spatial information along the predicted period of time t. For example, the positions of all the other agents within the vision range (which is much larger than the attention ranges) are measured based on their current relative velocities to the me agent.

Each row in a 2D array represents the spatial information for the area within a specific attention range at a specific point in time. In the demonstrated model, we use 3 levels of attention range with the distance of the first range R_0 from Agent 0 set to a proper value such that one agent can just fully occupy one visionary section at the boundary of R_0 as demonstrated by the red agent in Figure 2(b). R_1 and R_2 exponentially increase with regard to R_0.

While continuous space is transformed into discrete form to make computation feasible, our approach is inspired by the realistic way human process information through proper use of their attention as mentioned above. Spatial information is captured with more precision and thus given more attention weight within the immediate range R_0 of the agent. Information perceived in the current frame is assumed more important than information from predicted frames, thus more attention weight is given to the current frame. For illustration purpose, we demonstrate different attention weights with different darkness in Figure 2(b). The darker the colour is, the higher the attention weight on that area.

4.3 Pattern Specification

Spatial-temporal patterns are defined as certain *subsets* in the 3D array that emphasize the area of interest addressed by the attention in different situations.

Figure 3 demonstrates one example of a prototypical spatial-temporal pattern used for the selection of the *overtake* steering strategy. The pattern is highlighted as the subset within the 3D array; it reflects the agents perception on the current situation that *front center is blocked by some target agents with other oncoming agents from the right in the near future*. Thus, if the agents preferred speed is high, it may choose to *overtake* the agents in front from their left-hand side.

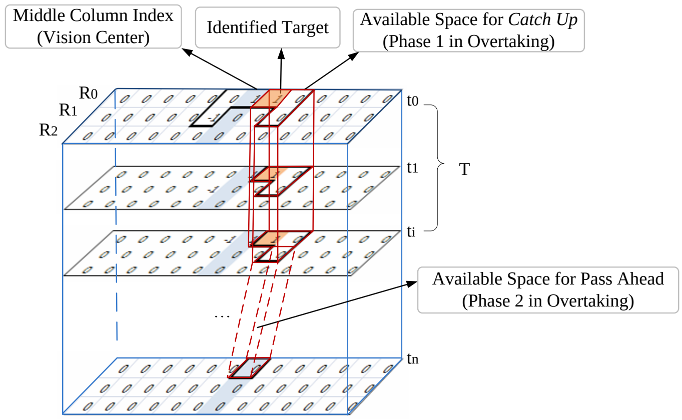


Fig. 3. An example of spatial-temporal pattern as a subset of the 3D array

In this case, a prototypical pattern to trigger the *overtake* steering strategy can be seen from the first frame of the 3D array in Figure 3. We can describe the pattern as *front center is blocked with available space aside*. It naturally follows the way that people describe the spatial configuration of a situation during their steering. Note that several prototypical patterns may trigger the same steering strategy. The modelers can specify the association of a prototypical pattern and its corresponding steering strategy to represent different experience base of different people.

5 Hierarchical Pattern Matching

In the pattern-matching process, an agent needs to check for the presence of the constituents of certain prototypical cases in the perceived spatial-temporal pattern from the current situation. The spatial-temporal patterns are now defined as subsets of the 3D array representation of the perceived situation as discussed in the last section. We adopt a hierarchical approach to match between such 3D patterns. Specifically, the 3D patterns are divided into slices of 2D spatial patterns with each slice corresponding to a different time instance. The matching result between two 3D patterns is aggregated from the matching results of these 2D patterns with different significance values. Since the attention weight varies along the spatial and temporal domains as discussed previously, such a hierarchical matching process naturally reflects the cognitive process of pedestrians with different significance to different areas. Thus, we can define the significance of similarity values between different 2D patterns accordingly.

More specifically, we start to search for the constituents of prototypical case in the first 2D array at current time step t_0. If a suitable match is found, the process continues to the next predicted frame slice a t_1. This process continues until such time as the pattern fails or succeeds to match. Matching success relates to the agent specific characteristic of commitment. The commitment parameter defines the number of slices of the pattern that must be successfully matched in order to consider the entire pattern matched. Those agents with high commitment require many matches; this intends to represent people who will only select strategies when they are confident of their success.

According to different steering strategies, the match between the 2D spatial patterns is also determined by different temporal constraints. Some require certain spatial patterns to exist for a period of time T and some just require their existence at a specific frame. In most cases, there is cohesion between subsequent 2D array matching processes. The temporal constraint T for the last matching process is used to guide the matching process in certain way, as will be illustrated with the example later, for the subsequent phases. Besides, T can also be used in empirical instruction to monitor the agents speed in locomotion. For example, if the prototypical temporal constraint T is smaller than the number of matched frames in the perceived 3D array, the speed of the agent is to be increased accordingly to meet the temporal constraint as specified by T.

Consider the pattern-matching process for the *overtake* steering strategy as an example shown in Figure 4. The execution of the overtake steering strategy can be generally modelled in three phases as *catch up*, *pass ahead* and *resume to original courses*. The prototypical pattern needs to represent the situations where overtake is usually triggered. Specifically, to trigger the attempt to *overtake*, *the agents center front should be blocked by some target and there should be available space that can accommodate the comfortable personal space beside the target* so that there is space for the agent to occupy during the *catch-up* phase. Such condition can be represented by prototypical patterns [xxx10xx] or [xx01xxx] in the first row of a 2D array as shown in Figure 4. The 2D arrays representing prototypical spatial patterns along different temporal frames to characterize how the overtake steering strategy is empirically executed in phases is shown on the left side of Figure 4; while the perceived spatial-temporal information from the current situation are represented in the 3D array on the right side of the figure. In this example, the 1 in the first row of the first 2D array in the prototypical pattern represents the group of target that has blocked me agents way, it should be around the middle column index in the array. The 0 represents the available space beside the target that is larger than me agents personal space. For example, if the personal space factor is 2, which means the agent generally keeps a full body size away from another agent, then the 0 in the prototypical pattern means that there are two continuous 0s in the array.

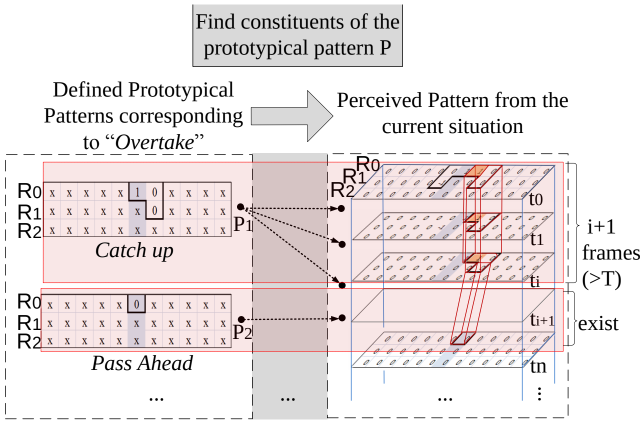


Fig. 4. Hierarchical pattern-matching process

To match such prototypical patterns with the current situation, we need to search for such patterns in the 3D array that formed to represent the situation. For the example, such patterns exist in the 3D array in R_0 at t_0 as highlighted in Figure4. Note that only the specific area of interest is considered in the pattern-matching process. This ensures our approach is capable of handling a certain degree of uncertainty in the situation. For example, in Figure 4 any area other than that highlighted area in the 3D array is not important to the decision-making process for *overtake*, thus values (represented as x in the prototypical patterns) in these areas do not affect the decision-making results.

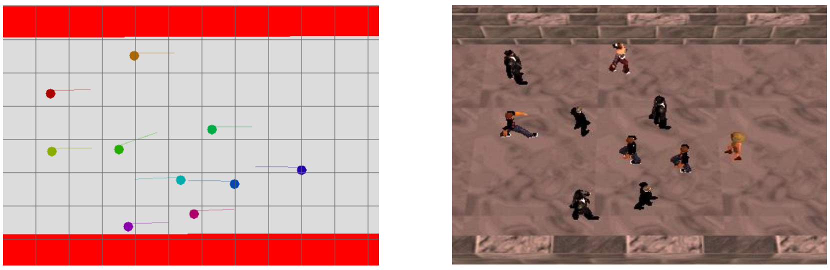
Along the temporal domain, such spatial patterns need to exist for certain frames (e.g., larger than T) so that the agent could reach the observed available space within the number of frames in the *catch up* phase. In Figure 4, spatial patterns for *catch up* last for $i + 1$ frames (i.e. from t_0 to t_i), and the agent starts from frame t_{i+1} to match the prototypical spatial patterns for *pass ahead* in the second phase of overtaking as shown in the second 2D array on the left side of Figure 4. The 0 in row R_0 represents the available space for me agent to *pass ahead* beside the target agent. Note that, the column index of the 0 changes to the middle column index from frame t_{i+1} onwards. This is because in the predicted frames, the agent should consider its relative position with the other agents. Since the patterns matched successfully for phase 1 in overtaking, the agent is to occupy the space beside the target and its subsequent steering behaviors in phase 2 should be based on the new position. In the decision-making process, these changes need to be taken into account though the agent has not started to execute the actions in practice.

As mentioned, matching success also relates to the agents specific characteristic of commitment. With high commitment level, agents are cautious and considerate in the situation; they will not start to overtake until a considerably sufficient number of frames of 2D arrays are matched with the prototypical cases. In this example, such agents will only start to overtake if the available space for all the 3 phases is perceived from the current situation. While agents with lower commitment level will start to overtake as long as the first few frames are matched for phase 1 in the overtaking process.

6 Simulation Results

We have implemented the newly improved pattern-based decision-making framework using the MASON multi-agent Toolkit [27]. Under the framework, we have designed a number of prototypical patterns in the model to mimic the experience of the agents as discussed in the previous sections. We test the pattern-based decision-making mechanism by tracking the steering behaviors of individual agents in some typical test cases and analyzing their steering choices together with their perceived spatial-temporal patterns. In particular, we investigate how they organize the information to form perceived patterns during navigation and how their steering choices are related with the patterns. The steering choices are explained in terms of the scheduling and execution processes of the steering strategies (e.g., *follow*, *overtake* and *side-avoid*).

To investigate individuals steering choices reflected by their velocity change in locomotion, we demonstrate their steering trajectories in 2D as shown in Figure 5(a). During the simulation, relevant attributes (including the position and velocity) of all the agents for each simulation step are kept in a log file, then the simulation can be replicated with the same steering behaviors in 3D with the GameStudio A7 engine as shown in Figure 5(b). For clearer illustration purpose, we demonstrate test cases in 2D in the following part.

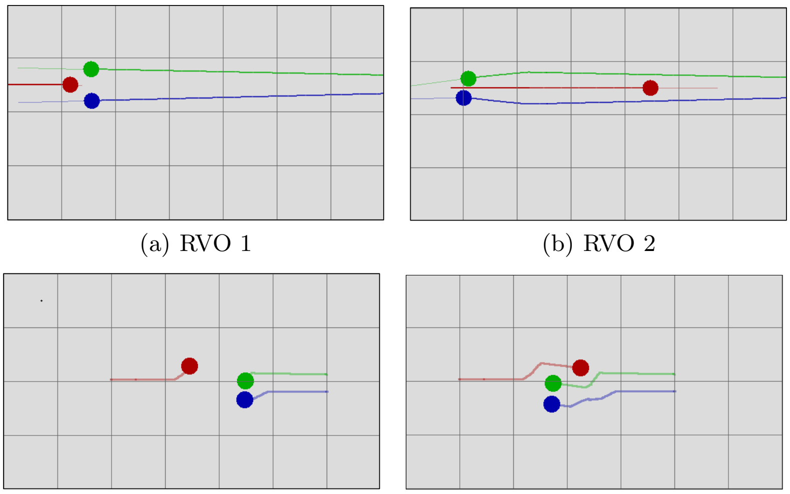


(a) (b)

Fig. 5. 2D and 3D demonstrations of simulation cases

It is still a challenging topic to evaluate the realism of steering behaviors from the simulation models up to date. Comparison is one of the most basic and common way to measure the performance. However, comparing motion of two different models is not a straight forward task; this is especially true when trying to indicate which model is more human-like. In this paper we do not propose a measure of how human-like of the behaviors our model can generate. Our results and comparison are provided for the reader to compare the output of both models and make their own assessment. Our analysis is based on our personal observations of human movement. The comparison does highlight that our model is capable of producing different behaviors when compared to the more mechanical motion planning systems. Specifically, , we compare the simulation results of our model with the RVO model (based on the latest RVO2 library [28]) under the same specific set of test cases. The RVO model is a representative motion control approach for steering behavior simulation. It achieves highly efficient collision free motion. The purpose of the comparison here is not to argue which is better or more efficient in generating collision-free steering behaviors in general cases. Instead, we want to demonstrate some scenarios where our approach is capable of producing more human-like behaviors based on the proposed pattern-based approach.

If we consider the situation shown in Figure 6, one agent is attempting to avoid two oncoming agents. It is a commonly observed scenario in any passageway situation. The steering trajectories of the agents are shown in the figure by a thicker line; the thinner line in front of an agent indicates its current moving velocity.

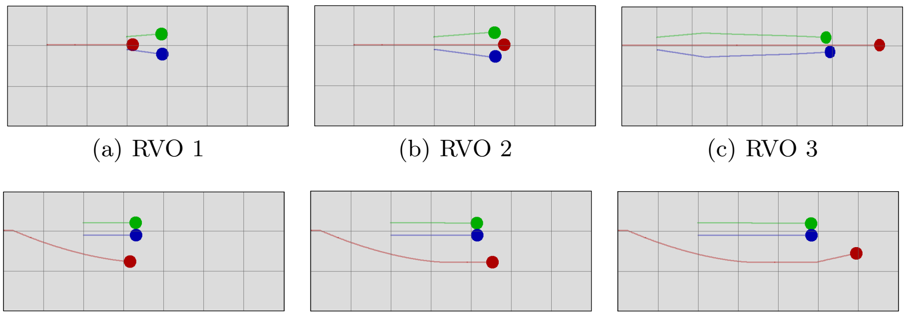


(a) RVO 1 (b) RVO 2

(c) PBM 1 (d) PBM 2

Fig. 6. Avoiding oncoming collisions in RVO model and our model

Results from the RVO model are shown in Figure 6(a) and 6(b). The group of two agents coming from the right side split (see Figure 6(a)) in order to avoid collisions and the agent starting from the left decreases its speed significantly until the other two agents have deviated to a collision free path. The agent then continues moving towards its goal with its initial speed. The results from our model are shown in Figure 6(c) and 6(d), where the single agent coming from the left will deviate its route proactively to avoid collision with the coming group of two agents. The group of two agents coming from the right side also change their velocities accordingly to avoid the collision. We examine the results from the pattern-based approach we adopt in the model. Both the individual and the group of two agents perceived the pattern that triggers the side-avoid steering strategy at 6(c) and start to execute the side-avoid steering strategy in the process as shown in 6(d). In real life, we usually observe that persons on their own or in a smaller group are likely to give way to a bigger group. With the simple test cases as shown in Figure 6, we want to demonstrate this behavior with our model, which is lacking in the current RVO models. In another test case shown in Figure 6, one agent is trying to overtake the other two agents in front.



(a) RVO 1 (b) RVO 2 (c) RVO 3

(d) PBM 1 (e) PBM 2 (f) PBM 3

Fig. 7. Overtaking a group of two agents in RVO model and our model

Simulation results from the RVO models are shown in Figure 7(a), 7(b) and 7(c). The agent behind reduces its speed when approaching to the agents in front, and the two agents in front will deviate to the side to give way to the agent coming from the back (see Figure 7(a)). After the agent coming from the back goes in front of them (see Figure 7(b)), the two agents steer back to their original course and continue moving towards their goals (see Figure 8 7(c)). The results from our model are shown in Figure 7(d), 7(e) and 7(f). The agent behind deviates its route to avoid collision with the other two agents in front through an overtaking behavior. It is shown clearly that there are three phases (catch up, pass ahead and resume to original course) as discussed in previous sections. In this case, the agent coming from behind perceives the two agents in front as a blockage in the vision center with available space beside them in the pattern. Thus, *overtake* steering strategy is triggered as shown in Figure 7(d) and the steering strategy is executed in three phases as shown in Figure 7(d), 7(e) and 7(f). In real-life situations corresponding to the situation as shown in this case, the group of two persons in front are less likely to proactively give way to the one behind due to two reasons: 1) they cannot see the person coming from behind; 2) they are in a group. On the other hand, the person behind is also likely to overtake the group of people in front from their side rather than cutting through them in-between due to the social norms. Though the test case is simple, it shows the unique feature of our approach to address peoples complex decision-making process during steering to certain extent through the comparison with the RVO model.

There are also some other test cases. Due to page limit, we do not illustrate them in the paper. While both models achieve collision avoidance through different steering choices, we have the following observations: Though RVO model generally achieves more smooth steering behavior at locomotive level, it can hardly reflect how pedestrians behave in similar situations as the test cases in real life. On the contrary, our approach generates more realistic steering behaviors in these situations. We can describe such behaviors naturally in terms of several steering strategies as *follow*, *overtake* or *side-avoid*. Besides, while RVO is general for all the agents in all the situations, our pattern-based approach can integrate with higher-level cognitive models through factors such as personal traits. It allows more flexibility for the modelers to specify different patterns or different association between patterns and steering strategies for different agents intuitively to model different experience of people. The less smooth locomotive movement generated by our model is partly because we mainly focus on the steering choices at the strategic level as discussed previously, thus our model currently has less control and fine-tuning directly at the locomotive level. This may be improved by specifying more constraints on the velocities of agents at locomotion based on the pattern-matching results in the future work. Though more comprehensive tests and systematic evaluation of our approach are still in progress, the current simulation results demonstrate some unique features of our model as discussed above.

7 Conclusions and Future Work

We present a pattern-based approach that aims to imitate how real pedestrians perceive and make steering decisions in daily-life situations. With the pattern-based approach, the complex cognitive processes involved in steering decision making are essentially transferred to pattern-matching processes between the perceived spatial-temporal patterns and the prototypical cases in agents experience base.

3D arrays have been used to capture some important spatial-temporal information. This representation allows modelers to intuitively specify various spatial-temporal patterns and also facilitate efficient information processing for making steering decisions. The hierarchal pattern matching mechanism aims to model how real pedestrians make sense of spatial temporal information and make steering decisions.

The simulation results are quite promising and demonstrate some unique features of this new approach. We plan to further refine the model under the pattern-matching mechanism and we are designing a comprehensive evaluation method for our model.

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